Applications of Iterative Blind Deconvolution Algorithms

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EXECUTIVE SUMMARY

In the text of our original proposal, we outlined the following tasks:

- Test existing IBD algorithms on various Hubble Space Telescope (HST) and Infrared Telescope Facility (IRTF) image data sets.
- Implement and test ideas that might improve IBD algorithms.
- Incorporate appropriate IBD algorithms as library routines for an IRTF data reduction pipeline.
- Study the efficacy of new IBD algorithms for upcoming releases of AIDA (Adaptive Image Deconvolution Algorithm) and build them into AIDA if appropriate.

More specifically, section 2 (Proposed Work) describes our plans to (a) investigate whether structure in the residuals (data minus model) can constrain the PSF (Point Spread Function), (b) make a switch within AIDA to use PIXON as its deconvolution engine, and (c) investigate stopping criteria for AIDA or IBD algorithms in general.

To date, we have just begun to run AIDA on test data sets. We have also set up an "algorithm test-bed" in IDL to see whether various penalty functions are effective in constraining PSF candidates in a back-propagation frame-work.

1. AIDA Test Runs

In August 2008, Co-I Marchis and colleagues M. Wong, E. Marchetti, P. Amico and S. Tordo obtained very sharp infrared images of Jupiter using the VLT (Very Large Telescope) Multi-Conjugate Adaptive Optics Demonstrator prototype. These images were the first MCAO data taken of an extended target.

There has been great interest in using deconvolution with images obtained from AO (adaptive optics) systems. The AO PSF is thought to be more stable than uncorrected PSFs, but it has long been realized that the wings of most AO PSFs often contain significant and variable amount of signal. Because the main peak of the PSF is often fairly stable, AO images should be compelling targets for IBD.

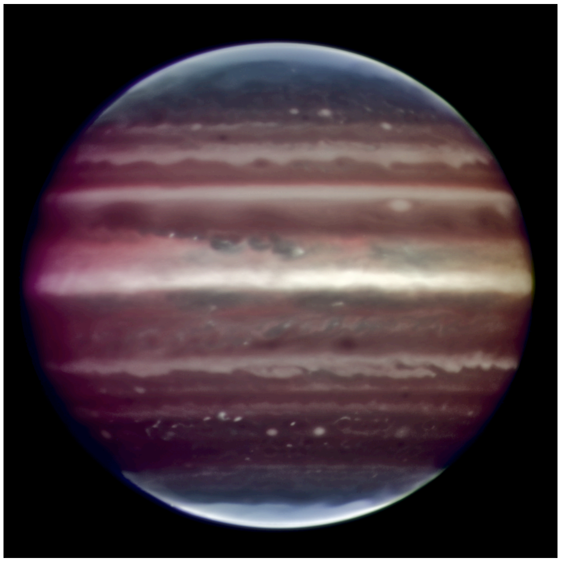

Fig. 1: Jupiter imaged in August 2008 from the VLT with their multi-conjugate adaptive optics demonstration prototype. The press release caption reads: *This false color image of Jupiter combines a series of images taken over 20 minutes on Aug. 17 by the Multi-Conjugate Adaptive Optics Demonstrator (MAD) prototype instrument mounted on ESO's Very Large Telescope. The image sharpening corresponds to seeing details about 300 kilometers wide on the surface of the giant planet. The observations were done at infrared wavelengths where absorption due to hydrogen and methane is strong. This absorption means that light can be reflected back only from high-altitude hazes, and not from deeper clouds. These hazes lie in the very stable upper part of Jupiter's troposphere, where pressures are between 0.15 and 0.3 bar. Mixing is weak within this stable region, so tiny haze particles can survive for days to years, depending on their size and fall speed. Additionally, near the planet's poles, a higher stratospheric haze (light blue regions) is generated by interactions with particles trapped in Jupiter's intense magnetic field.*

Credit: ESO/F. Marchis, M. Wong, E. Marchetti, P. Amico, S. Tordo

Co-I Marchis and colleague Mike Wong (UC Berkeley) attempted to further sharpen their Jupiter images using AIDA. At present, the lack of bright on-chip PSFs is hampering thier efforts to sharpen these AO images.

2. A Back-Propagation Test-Bed

We are interested in a test-bed environment to let us rapidly implement and evaluate schemes that potentially constrain PSF candidates. We have begun with a back-propagation framework, implemented in IDL, based on the first chapter on Jon Claerbout's book *Image Estimation by Example* (also known by its earlier acroname, *GEE*), available online (http://sepwww.stanford.edu/data/media/public/sep//prof/index.html).

In general, this test-bed iteratively examines *residuals* from the mismatches between the current model and the data, then generates updates to the model from the residuals.

We start with a typical assumption, that an observed image (D) is a convolution of the true image (IM) and a PSF, with noise added.

$$DATA = IM \otimes PSF + NZ \qquad (1)$$

Since convolution is a linear operation, we can represent the convolution as

$$D = \sim\boldsymbol{F}x \qquad (2)$$

where D is a vector of the *DATA* pixel values, x is a vector of the *IM* pixel values, and $\boldsymbol{F}$ is a matrix that performs a convolution with the PSF, and we understand that the noise term will show up as non-zero residuals, $R = D - \boldsymbol{F}x$. It is our convention that variables in data space (D, R) are capitalized.

If we unwrap the D and x arrays into 1-dimensional vectors, the $\boldsymbol{F}$ matrix will be enormous and circulant (each row identical to the row above it except for a one-column shift). In practice, however, we never need to allocate and evaluate the $\boldsymbol{F}$ matrix, since we can always generate the product ($\boldsymbol{F}x$) using FFTs. In Claerbout's book, he uses the adjoint[1] of $\boldsymbol{F}$ to map residuals back into updates to the parameters (x). We have to remember that the adjoint of CONVOLUTION is the CROSS-CORRELATION operation, and both can be implemented with FFTs.

Example:

Here is a test case with three point sources in a 32 x 32 pixel window. We've made a PSF that is a gaussian with a width of 3.25 pixels. The synthetic *DATA* array is the convolution of the three point sources with the addtion of some normally distributed random noise (Fig. 2).

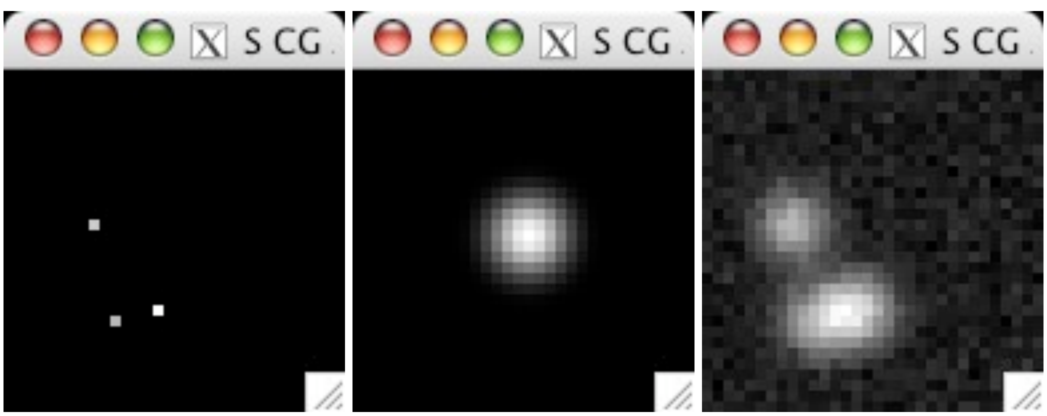

Fig. 2: The true image (left) made up of three point sources, the PSF (middle), and the DATA (right).

In the three images below, we show the current model, the residuals, and the conjugate directions (the deltas to be applied to the model) after one iteration.

[1] *Adjoint* has many definitions. In this context, the *adjoint* of a matrix is its conjugate transpose (or just the transpose if the matrix is real).

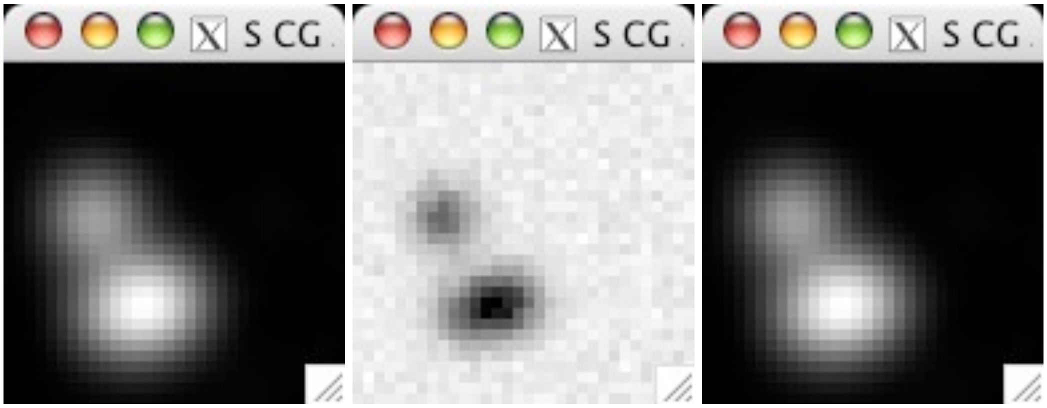

Fig. 3: After ONE iteration, the current image (left), the residuals (middle), and the current corrections to the curent image (right). The initial image (left) started off as zeros befroe the first iteration.

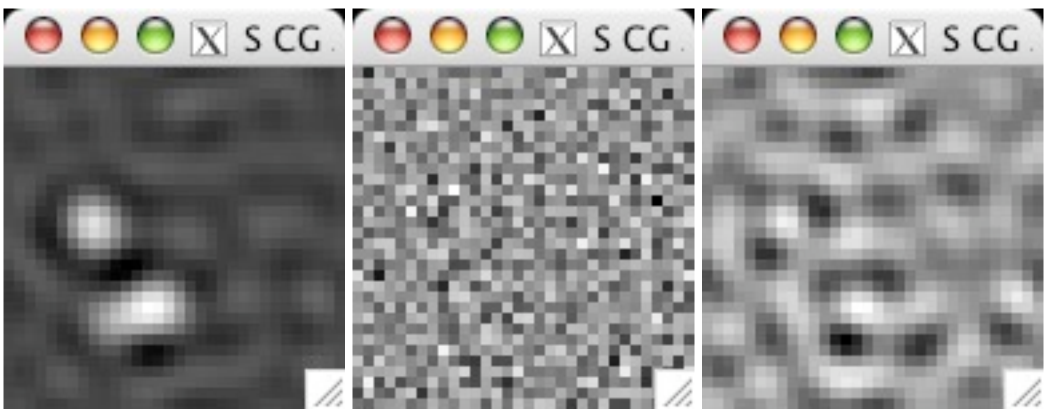

Fig. 4: After FIVE iterations, the current image (left) is starting to get sharper. It *should* tend toward the true image (the three points in the left panel of Fig. 2). The residuals (middle) are starting to look more like white noise (good), but the current image has developed negative regions, especially around the sources. The updates (right) to the current model are continuing to push some pixels to negative values.

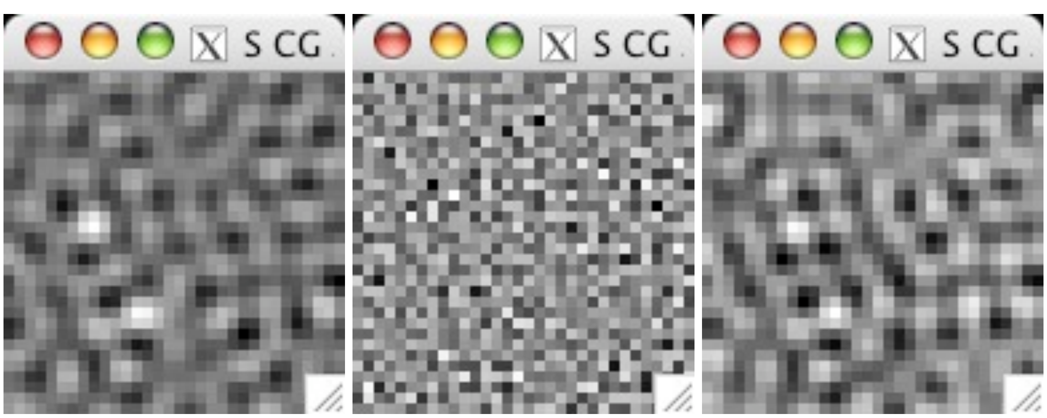

Fig. 5: After 100 iterations, we see that the *IM* array (left) has developed a significant checkerboard pattern. The PSF smooths out the adjacent negative and positive pixels such that the residuals are small and smooth.

Figure 5 dramatically shows us what our next step must be: we must incorporate regularization into the iterative process to enforce conditions that we know must be true. Two of these, positivity of the image and local regions of support around the sources, are commonly used (and are part of AIDA, IDAC and MISTRAL). We plan to add another constraint, non-uniform structure in the residuals, to map back into deltas to the model.

3. Future Directions

This section describes some progammatic changes that we are considering for the remaining portion of this grant.

- Because of delays between UC Berkeley and SwRI grant offices in implementing a subcontract to UC Berkeley, this project got off to a late start. PI Young met with Co-I Rick Puetter in September 2008 and Co-I Franck Marchis in December 2008, even though the nominal start date was January 2008. We will likely request a 1-year no-cost extension as a result.
- At Harvey Mudd College (Clarement, CA), there is a decades-old *clinic program* in which teams of four students work on collective projects for third party entities (like SwRI). PI Young has had good experience with this program. All Harvey Mudd students take a programming class in Python, the language in which AIDA is written. We would like to hire a clinic team to implement modifications to AIDA and to document and package AIDA to make its distribution as simple and useful as possible.

  The cost of a clinic team is $45K. We will apply for E/PO funds to address $15K of that cost, and re-direct $30K of funding from PI Young and (to a lesser extent) Co-I Marchis to cover the cost of the clinic team. While E/PO funds are generally not intended for undergraduate research, there is an exception for *teams* of undergraduates who will be working together in a mode that models aspects of SMD mission experience.